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A hybrid large neighborhood search for the static multi-vehicle bike-repositioning problem

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ABSTRACT

This paper addresses the multi-vehicle bike-repositioning problem, a pick-up and delivery vehicle routing problem that arises in connection with bike-sharing systems. Bike-sharing is a green transportation mode that makes it possible for people to use shared bikes for travel. Bikes are retrieved and parked at any of the stations within the bike-sharing network. One major challenge is that the demand for and supply of bikes are not always matched. Hence, vehicles are used to pick up bikes from surplus stations and transport them to deficit stations to satisfy a particular service level. This operation is called a bike-repositioning problem. In this paper, we propose a hybrid large neighborhood search for solving the problem. Several removal and insertion operators are proposed to diversify and intensify the search. A simple tabu search is further applied to the most promising solutions. The heuristic is evaluated on three sets of instances with up to 518 stations and five vehicles. The results of computational experiments indicate that the heuristic outperforms both CPLEX and the math heuristic proposed by Forma et al. (2015) [Transportation Research Part B 71: 230–247]. The average improvement of our heuristic over the math heuristic is 1.06%, and it requires only a small fraction of the computation time.

1. Introduction

Bikes constitute a green and healthy mode of transportation, and have thus drawn increased attention in recent years. Research topics include bike trip estimation (de Chardon and Caruso, 2015), bike network design (Chow and Sayarshad, 2014; Lin and Yang, 2011; Lin et al., 2013), bike network flow analysis (Kitthamkesorn et al., 2016), bike service level analysis (Raviv and Kolka, 2013), bike safety (Lawson et al., 2013), bike redistribution strategies (Nair and Miller-Hooks, 2011), and bike repositioning. In bike repositioning, vehicles are deployed to pick up and transport bikes from stations with an excess of bikes to stations with an insufficient number. Table 1 summarizes the literature on bike-repositioning problems according to operation type, number of repositioning vehicles used, and problem objectives.

In terms of operation type, the literature can be roughly classified into two categories: static and dynamic. Static repositioning problems consider night-time operations and scenarios in which demand is low or the system is closed, meaning

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Table 1
Summary of the bike-repositioning problem literature.

Reference	Type	No. of vehicles	Objective
Benchimol et al. (2011)	Static	1	Minimize total travel cost
Caggiani and Ottomanelli (2012)	Dynamic	>1	Minimize relocation and lost user cost
Contardo et al. (2012)	Dynamic	>1	Minimize total unmet demand
Lin and Chou (2012)	Static	>1	Minimize total travel time or distance
Chemla et al. (2013)	Static	1	Minimize total travel distance
Di Gaspero et al. (2013a)	Static	>1	Minimize the weighted sum of total travel time and total absolute deviation from the target number of bikes
Nair et al. (2013)	Static	1	Minimize total redistribution cost
Raviv et al. (2013)	Static	>1	Minimize the weighted sum of total travel time and penalty cost
Schuijbroek et al. (2013)	Static	>1	Minimize maximum tour length
Erdoğan et al. (2014)	Static	1	Minimize travel and handling costs
Ho and Szeto (2014)	Static	1	Minimize total penalty cost
Kloimüllner et al. (2014)	Dynamic	≥1	Minimize the weighted sum of unfulfilled demand, absolute deviation from the target fill level, total number of loading instructions, and total drive time
Forma et al. (2015)	Static	>1	Minimize the weighted sum of total travel time and penalty cost
Rainer-Harbach et al. (2015)	Static	≥1	Minimize the weighted sum of the total absolute deviation from the target number of bikes, total number of loading/unloading activities, and overall travel time required for all routes
Szeto et al. (2016)	Static	1	Minimize the weighted sum of unmet customer demand and operational time on the vehicle route

that the change in demand is negligible. Dynamic repositioning problems mainly consider daytime operations and scenarios that take real-time system usage into account. As shown in Table 1, most studies focus on static repositioning problems because such problems are already difficult to analyze and solve without introducing further complexities. Ho and Szeto (2014) pointed out that static repositioning problems are NP-hard, and are more difficult to solve than classical routing problems because of the presence of pick-up and drop-off quantities as decision variables. An understanding of static repositioning problems and the algorithms developed for them is useful in addressing more difficult dynamic repositioning problems.

The objectives considered in the literature vary. As shown in Table 1, both single and weighted sum objectives are considered. The objectives are formed by either a single measure of effectiveness (e.g., total unmet demand) or a weighted combination of measures of effectiveness (e.g., the weighted sum of unfulfilled demand, the absolute deviation from the target fill level, the total number of loading instructions, and total drive time). Moreover, travel time or distance, user dissatisfaction, and penalty cost are commonly used as sole or partial components in the objective function. The choice of objectives should be determined by the application of bike-sharing operations. The operator's concern normally governs the choice of objective. Meanwhile, some objectives are more general than others. For example, minimizing total penalty cost is more general than minimizing total user dissatisfaction or the sum of the deviations from the target number of bikes in each station because we can choose a penalty function that assigns a value of zero to the level equal to or greater than the demand level and a very large number to other levels to replicate the effect of minimizing total user dissatisfaction. Similarly, we can select a penalty function that assigns a value to a level equal to the absolute difference between that level and the target level to replicate the effect of minimizing the sum of deviations.

The literature can also be classified according to the number of vehicles employed. In terms of formulation, multiple-vehicle repositioning problems are straightforward extensions of single-vehicle problems. However, it is more realistic to consider multiple-vehicle repositioning problems. Some studies that consider multiple vehicles (Alvarez-Valdes et al., 2016) allow each station to be visited by multiple vehicles more than once, whereas others (Dell'Amico et al., 2014) allow each station to be visited only by exactly one vehicle. The main challenge in addressing multi-vehicle than single-vehicle repositioning problems is developing efficient solution methods to handle the larger solution space arising from the presence of more vehicles and the possibility of multiple visits to a station. Direct applications of the solution techniques for the single-vehicle case cannot search the solution space efficiently.

Exact methods such as branch-and-cut algorithms (see Dell'Amico et al., 2014; Erdoğan et al., 2015, 2014) have been used to solve repositioning problems. However, such methods are intractable for large, realistic repositioning problems. The literature (e.g., Ho and Szeto, 2014; Raviv et al., 2013) has also illustrated this point via numerical experiments. Therefore, most studies to date have focused on developing inexact methods to obtain good solutions using small computing time. A brief summary of inexact solution methods follows (see Table 2).